Practical Model Reference Robust Control for Pneumatic Servo System[†]

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A practical control scheme of model reference robust control (MRRC) for pneumatic servo system is introduced in this paper. As an important driving element, the pneumatic cylinders are widely used in industrial applications. It is well known the control problem of pneumatic cylinder becomes complex in varying load, travel and environment temperature, because it contains unknown parameters, possible nonlinear uncertainties and additive bound disturbances. The proposed control scheme is essential to achieve the robust stability and good performance for time-varying and nonlinear systems. The controller requires only measured input and output signals of system, rather than the full state feedback. In order to suit for practical application the neural control parameters estimator is led into the controller. Compared with MRAC, it makes the controller become simple.

Key Words : model reference robust control, pneumatic cylinder, nonlinear plant, neural network, external disturbance

1. Introduction

Robust feedback controllers are the most common control schemes used for the control of nonlinear plant with uncertain dynamics. Their popularity is due to the simplicity of their structures as well as the familiarity of designers with feedback control theory.

In most robust feedback control schemes^{4),5)}, the authors either use state feedback to place the poles sufficiently far in the left-half-plane, or insert a feedback compensator in the closed loop feedback control system to cancel the effects of system uncertainties and guarantee the stability of the closed loop system. However, for the most of these schemes, the transient error response of the closed loop system can not be specified directly in the design. Therefore, the design of the high quality tracking controller which can guarantee good system performance is still a challenging topic in the servo control fields^{6),7),8)}.

It is worth mentioning that other nonlinear controllers such as high-gain control and sliding mode control are also based on Lyapunov designs and have similar robustness properties except that high-gain control may require excessively large control effect and sliding mode control is inherently discontinuous.

Qu has put forward the conception of MRRC^{1),2),3)}, and given the controller design method from minmax Lyapunov design for continuous control system. Qu's results make us have the capability to handle with the control problem as MRAC using

robust control theory.

In this paper, to apply MRRC to practical control problems and improve the control property of pneumatic servo system, we lead a neural estimator into the controller which can estimate the control parameters of system and update the parameters error bounds used in robust controller on-line. It improves the output tracking accuracy and system robustness. Then we put forward the control model for plant with nonlinear uncertainties, which makes MRRC controller suit for control problem of pneumatic servo system. The experiments for practical model can prove the effectiveness of this control scheme.

This paper is organized as follows: Section 2 contains the configuration of pneumatic servo system. In Section 3 the MRRC is introduced simply. The system controller and control parameters estimator are given in Section 4. The results of simulation and experiment are shown in Section 5. In Section 6, we discuss the conclusions of this control scheme.

2. Configuration of pneumatic servo system

Fig. 1 shows the configuration of the pneumatic servo system. The system is primarily composed of the pneumatic cylinder, a 32 bit personal computer with an 80486 CPU and an associated arithmetic coprocessor, two 12-bit D/A converters, two servo amplifiers of the voltage-current transformation type, and two electro-pneumatic proportional valves.

The pneumatic cylinder (CA1BQ63-300: SMC Corporation) is a low friction type. Its minimum pressure is 0.01 MPa, the inside diameter is $\phi 63$, and the stroke is 300mm. A load mass 10kg is usually connected to the tip of a position rod. The electro-pneumatic proportional valve is a pressure proportional control

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valve(VEP3120-1 : SMC Corporation) of 3 port type. The

Fig. 1 Configuration of the pneumatic servo system

position measurement is carried out by a magnetic scale sensor whose resolving power is $10\mu\text{m}$ (SR10-100A : SONY Corporation).

If we define the system input as $p(t) = P_A - P_B$ and the position of piston as $y(t)$, usually, we can describe the dynamic equation of pneumatic cylinder as follows:

$$\ddot{y}(t) + \frac{D}{M} \dot{y}(t) = \frac{A}{M} [u(t) + d(y, \dot{y}, t)] \quad (1)$$

where

A : area of piston

D : sticky friction parameter

M : load mass

$d(y, \dot{y}, t)$: the lumped disturbance and uncertainty caused by the uncertain friction dynamics, air compression dynamics and unknown external disturbance.

As the uncertain friction dynamics is always bounded, for the further analysis, we assume the existence of a continuous, nonnegative, known function $\rho(y, t)$ such that

$$|d(y, \dot{y}, t)| < \rho(y, t) \quad (2)$$

3. Model reference robust control

According to Qu's model reference robust control theory, we can describe the plant as (3)

$$y^{(n)}(t) + a_{p1} y^{(n-1)}(t) + \dots + a_{pn} y(t) = b_{p0} [u^{(m)}(t) + b_{p1} u^{(m-1)}(t) + \dots + b_{pm} u(t) + d_1(y, t)] \quad (3)$$

where $m \leq n$, $d_1(y, t)$ is the external disturbance and can be bounded by a nonlinear function defined explicitly by the output y and time t . When the disturbance is absent we have the transfer function relationship as

$$\begin{aligned} \left. \frac{Y(s)}{U(s)} \right|_{d_1=0} &= b_{p0} \frac{s^m + b_{p1}s^{m-1} + \dots + b_{pm}}{s^n + a_{p1}s^{n-1} + \dots + a_{pn}} \\ &\triangleq k_p \frac{B_p(s)}{A_p(s)} \triangleq G_p(s) \end{aligned} \quad (4)$$

The control problem investigated in MRRC is the model following problem for which the output of the plant (3) tracks the output of a reference model for any given reference signal $r(t)$ in the presence of disturbance $d_1(y, t)$. The reference model is described by the following transfer function

$$\begin{aligned} \frac{Y_m(s)}{R(s)} &= b_{m0} \frac{s^m + b_{m1}s^{m-1} + \dots + b_{mpm}}{s^n + a_{m1}s^{n-1} + \dots + a_{mn}} \\ &\triangleq k_m \frac{B_m(s)}{A_m(s)} \triangleq G_m(s) \end{aligned} \quad (5)$$

where $Y_m(s)$ and $R(s)$ are Laplace transforms of $y_m(t)$ and $r(t)$, respectively, $k_m > 0$ and $r(t)$ is a bounded reference input. It is assumed that both $A_m(s)$ and $B_m(s)$ are coprime Hurwitz polynomials.

To achieve perfect tracking using only input and output data, a strictly positive real (SPR) transfer function is generated from the transfer function of the reference model. Define

$$\bar{G}_m(s) = G_m(s) \alpha(s) \triangleq k_m \frac{\bar{B}_m(s)}{A_m(s)} \quad (6)$$

where $\alpha(s)$ is a monic, Hurwitz polynomial in s of degree $m - n - 1$, and $G_m(s)$ is the reference model. If $G_m(s)$ has relative degree larger than the relative degree of $G_p(s)$, $\alpha(s)$ is chosen such that $\bar{G}_m(s)$ has relative degree one. It is assumed that $\bar{G}_m(s)$ is SPR

Fig. 2 Block diagram of model reference robust control

The block diagram of MRRC is shown in Fig. 2. According to it, the following system variable can be defined.

I: Auxiliary signal $w(t)$

$$w(t) = [r(t), y(t), w_1^T(t), w_2^T(t)]^T \quad (7)$$

where

$$\dot{w}_1(t) = A_0 w_1(t) + B_0 u(t)$$

$$\dot{w}_2(t) = A_0 w_2(t) + B_0 y(t)$$

and $w_1(t) \in R^{(n-1)}$, $w_2(t) \in R^{(n-1)}$ are state vectors, $A_0 \in R^{(n-1) \times (n-1)}$ is a matrix such that $\det[sI - A_0] = \bar{B}_m(s)$ and $B_0 \in R^{(n-1)}$ is a constant vector such that the pair (A_0, B_0) is controllable.

II: The output tracking error $e(t)$

$$e(t) = y_m(t) - y(t) \quad (8)$$

III: The states of the controllable canonical realization of the transfer function $1/\alpha(s)$ can be defined. That is, if

$$\alpha(s) = s^l + \alpha_1 s^{l-1} + \dots + \alpha_l s^0 + \dots + \alpha_l$$

we define

$$\begin{aligned}
z_1 &= u_R / \alpha_1 \\
\dot{z}_i &= z_{i+1} \quad i = 1, 2, \dots, l-1 \\
\dot{z}_l &= -\alpha_1 z_1 - \dots - \alpha_{l-1} z_{l-1} + u_R \\
&= -\alpha_1 z_1 - \dots - \alpha_{l-1} z_{l-1} + u - \vartheta^T w(t)
\end{aligned} \quad (9)$$

where $l = n - m - 1$.

IV: The auxiliary filter vector $\bar{w}(t)$

$$\bar{w}(t) = [\bar{r}(t), \bar{y}(t), \bar{w}_1^T(t), \bar{w}_2^T(t)]^T \quad (10)$$

where

$$\begin{aligned}
\bar{r}(t) &= \frac{1}{\alpha(s)} r(t), \quad \bar{y}(t) = \frac{1}{\alpha(s)} y(t) \\
\bar{w}_1(t) &= \frac{1}{\alpha(s)} w_1(t), \quad \bar{w}_2(t) = \frac{1}{\alpha(s)} w_2(t)
\end{aligned} \quad (11)$$

V: Control parameter error vector $\bar{\vartheta}$

$$\bar{\vartheta} = \vartheta^* - \vartheta \quad (12)$$

where ϑ^* is the desired controller parameter, and ϑ is an arbitrary estimate of ϑ^* .

VI: Let $\psi(y, t)$ be a continuous function. Then $BND(\|\psi(y, t)\|)$ is a known, continuous and nonnegative function that bounds the magnitude (or Euclidean norm) of $\psi(y, t)$. That is, for all $(y, t) \in R \times R^+$

$$\|\psi(y, t)\| \leq BND(\|\psi(y, t)\|) \quad (13)$$

Thus the auxiliary control variables can be defined as follows:

$$v_1 = \frac{\mu_1(e, y, u, t) \|\mu_1(e, y, u, t)\|}{2\|\mu_1(e, y, u, t)\|^2 + \delta_1} g_1(y, u, t) \quad (14)$$

where $\mu_1(e, y, u, t) = e(t)g_1(y, u, t)$ and

$$\begin{aligned}
g_1(y, u, t) &= 2BND(\|\bar{\vartheta}\|) \times \|\bar{w}(t)\| \\
&+ 2BND\left(\left|\frac{1}{\alpha(s)} \times \left(1 - \frac{D_1(s)}{\bar{B}_m(s)}\right) \times d_1(y, t)\right|\right)
\end{aligned} \quad (15)$$

The following l mappings are then defined by

$$\begin{aligned}
v_i &= e + v_{i-2} - z_{i-2} + v_{i-1} - z_{i-1} \\
&+ \frac{\mu_i(e, y, u, t) \|\mu_i(e, y, u, t)\|}{2\|\mu_i(e, y, u, t)\|^2 + \delta_i} g_i(y, u, t)
\end{aligned} \quad (16)$$

and

$$\begin{aligned}
v_{l+1} &= \alpha_1 z_l + \alpha_2 z_{l-2} + \dots + \alpha_l z_1 + v_{l-1} - z_{l-1} + v_l - z_l \\
&+ \frac{\mu_{l+1}(e, y, u, t) \|\mu_{l+1}(e, y, u, t)\|}{2\|\mu_{l+1}(e, y, u, t)\|^2 + \delta_{l+1}} g_{l+1}(y, u, t)
\end{aligned} \quad (17)$$

For $i = 2, 3, \dots, l$ with

$$g_i(y, u, t) = 2BND(\|\dot{v}_{i-1}\|) \quad (18)$$

$$\mu_i(e, y, u, t) = (v_{i-1} - z_{i-1}) g_i(y, u, t) \quad (18)$$

$$g_{l+1}(y, u, t) = 2BND(\|\dot{v}_l\|) \quad (19)$$

$$\mu_{l+1}(e, y, u, t) = (v_l - z_l) g_{l+1}(y, u, t) \quad (19)$$

Quotation: If we choose the robust control $u(t)$ as

$$u(t) = \vartheta^T w(t) + u_R(t); \quad u_R(t) = v_{l+1}(t) \quad (20)$$

the plant output tracking error $e(t)$ is globally uniformly ultimately bounded. That is, as time approaches infinity, the

magnitude of the output tracking error becomes no larger than a constant δ which can be made arbitrarily small by choosing the design parameters δ_i small enough. Furthermore, the robust control $u(t)$ is continuous and globally, uniformly bounded²⁾.

4. Practical MRRC for pneumatic servo system

On the basis of the dynamical model of pneumatic cylinder described in Eq. (1), it can be thought as a classical second order control element, take the lumped disturbance, nonlinear factor and uncertainty described by a nonlinear unknown function $d(y, \dot{y}, t)$ into account, we can design the practical MRRC controller for pneumatic servo system.

Fig. 3 Block diagram of the practical MRRC

4.1 Definitions of plant and reference model

According to the dynamical model of pneumatic cylinder described in Eq. (1), we can rewrite the linear part of Eq. (1) as follows:

$$G_p(s) = k_p B_p(s) / A_p(s) = k_p / (s^2 + a_{p1}s + a_{p2}) \quad (21)$$

where $k_p = A / M$, $k_p > 0$, $a_{p1} = D / M$ and $a_{p2} = 0$. On the other hand, the nonlinear part can be described by the lumped disturbance and uncertainty $d(y, \dot{y}, t)$.

The reference model can be defined as

$$G_m(s) = k_m B_m(s) / A_m(s) = k_m / (s^2 + a_{m1}s + a_{m2}) \quad (22)$$

In the case that $G_m(s)$ is not SPR, let $\alpha(s) = s + \alpha_0$ and assume that $\alpha(s)G_m(s)$ is SPR.

Fig. 4 Block diagram of control parameters estimator

4.2 On-line control parameters estimator

It is noted in 2) that the tracking error can be made smaller by choosing a small value of the design parameters δ_i . If δ_i is too small, however, the output of the robust controller may change rapidly and has a large magnitude. Since the parameters error bounds and the lumped disturbance and uncertainty bound function are usually conservative, the design parameter δ_i can not be set too small. In this paper, in order to overcome this

shortage and improve the control performance, we lead the controller estimator to calculate the parameter bounds into the practical controller.

Fig. 4 shows the block diagram of control parameters estimator formed by a linear neural network, where W_i is the coupling coefficient between an input layer node and a hidden layer node V_i is the coupling coefficient between a hidden layer node and an output layer node. O_N is the output of neural network. If we define

$$\vartheta(t) = V_i(t)[W_0(t), W_1(t), W_2(t), W_3(t)]^T \quad (23)$$

we have

$$u_e(t) = O_N(t) = \vartheta^T(t)w(t) \quad (24)$$

where $\vartheta(t)$ is the estimate of ϑ^* in instant t . Network can be trained by BP algorithm 8) as follows:

$$\begin{aligned} V_i(t) &= V_i(t-1) + \Delta V_i(t) \\ W_i(t) &= W_i(t-1) + \Delta W_i(t) \end{aligned} \quad (25)$$

where

$$\begin{aligned} \Delta V_i &= -\eta(\partial E / \partial V_i) \\ \Delta W_i &= -\eta(\partial E / \partial W_i) \end{aligned} \quad (26)$$

and E is the auxiliary error, it can be defined as

$$E(t) = \frac{1}{2} [y(t) - y_m(t)]^2 \quad (27)$$

From Fig. 4, taking control parameters estimator into account, we can rewrite the control of closed loop system as

$$u(t) = u_R(t) + u_e(t) \quad (28)$$

4.3 Design of practical MRRC controller

On the basis of definitions of pneumatic cylinder and reference model in Eqs.(21) and (22) we can design the MRRC controller as follows:

Step 1:

Define system variables as

$$\begin{aligned} A_0 &= -\alpha_0, B_0 = 1, D_1(s) = \vartheta_1, \\ D_2(s) &= \vartheta_0(s + \alpha_0) + \vartheta_2 \\ \vartheta &= [k, \vartheta_0, \vartheta_1, \vartheta_2]^T \end{aligned}$$

where ϑ is the arbitrary estimate of ϑ^* . It is estimated by control parameters estimator described in 4.2 and used to bound $\bar{\vartheta} = \vartheta^* - \vartheta$ in each instant, where $\vartheta^* = [k^*, \vartheta_0^*, \vartheta_1^*, \vartheta_2^*]^T$. For the estimate of the parameter bounds, we assume that $\text{sign}(k^*)$ and $\text{sign}[\vartheta^*]$ are known in this paper.

Step 2:

Generate, if desired, the auxiliary signals

$$\begin{aligned} \dot{w}_1 &= -\alpha_0 w_1 + u & \dot{w}_2 &= -\alpha_0 w_2 + y \\ \dot{r} &= -\alpha_0 r + r & \dot{y} &= -\alpha_0 y + y \\ \dot{\bar{w}}_1 &= -\alpha_0 \bar{w}_1 + w_1 & \dot{\bar{w}}_2 &= -\alpha_0 \bar{w}_2 + w_2 \\ \dot{z} &= -\alpha_0 z + z \end{aligned} \quad (29)$$

Step 3:

Determine the control from the recursive mapping

$$\begin{aligned} v_1 &= \frac{\mu_1(e, y, u, t) \left| \mu_1(e, y, u, t) \right|}{2 \left(\left| \mu_1(e, y, u, t) \right|^2 + \delta_1 \right)} g_1(y, u, t) \\ &= \frac{e |e| g_1^3}{2(e^2 g_1^2 + \delta_1)} \end{aligned} \quad (30)$$

where $\delta_1 > 0$ is a constant, and $\mu_1(e, y, u, t) = e g_1(y, u, t)$ and

$$\begin{aligned} g_1(y, u, t) &\triangleq BND(\tilde{k}^2) + BND(\tilde{r}^2) + BND(\tilde{\vartheta}_0^2) + \tilde{y}^2(t) \\ &\quad + BND(\tilde{\vartheta}_1^2) + BND(\tilde{\vartheta}_2^2) + \tilde{w}_1^2(t) + \tilde{w}_2^2(t) \\ &\quad + 2 \int_0^t \exp[-\alpha_0(t-\tau)] \rho(y, \tau) d\tau + BND(\vartheta_1) \\ &\quad \times 2 \int_0^t (t-\tau) \exp(-\alpha_0 \tau) \rho(y, \tau) d\tau \end{aligned} \quad (31)$$

Thus, we can rewrite the control of overall system as:

$$\begin{aligned} u(t) &= \vartheta^T w(t) + u_R \\ &= \vartheta^T w(t) + \alpha_0 z(t) + e(t) + v_1(t) - z(t) \\ &\quad + \frac{\mu_2(e, y, u, t) \left| \mu_2(e, y, u, t) \right|}{2 \left(\left| \mu_2(e, y, u, t) \right|^2 + \delta_2 \right)} g_2(y, u, t) \end{aligned} \quad (32)$$

where $\delta_2 > 0$ is a constant,

$$\mu_2(e, y, u, t) = (v_1 - z) g_2(y, u, t) \quad (33)$$

$$BND[\tilde{k}(t)] = |k^*(0) - k(t)| \quad (34)$$

$$BND[\tilde{\vartheta}_i(t)] = |\vartheta_i^*(0) - \vartheta_i(t)| \quad \text{for } i = 0, 1, 2 \quad (35)$$

$$g_2(y, u, t) = 2BND(\dot{v}_1) \quad (36)$$

and then the parameters $k^*(0)$ and $\vartheta_i^*(0)$ can be selected such that

$$\text{sign}[k^*(0)] = \text{sign}[k^*], |k^*(0)| \geq |k^*| \quad (37)$$

$$\text{sign}[\vartheta_i^*(0)] = \text{sign}[\vartheta_i^*], |\vartheta_i^*(0)| \geq |\vartheta_i^*| \quad i = 0, 1, 2 \quad (38)$$

To implement the MRRC, we have to find a bounding function for $\dot{v}_1$. It follows that

$$\frac{d v_1}{d t} = \frac{\partial v_1}{\partial e} \frac{d e}{d t} + \frac{\partial v_1}{\partial g_1} \frac{d g_1}{d t} \quad (39)$$

in which every term is well defined and can be easily bounded.

It follows that

$$\begin{aligned} BND(\dot{e}) &\triangleq BND(b_{\rho 0}) (|z| + 0.5 g_1(y, u, t) \\ &\quad + \int_0^t h(t-\tau) [|z| + 0.5 g_1(y, u, \tau)] d\tau \end{aligned} \quad (40)$$

where $h(t)$ is the inverse Laplace transform of $1 - s \bar{G}_m(s)$ and $\bar{G}_m(s) = (s + \alpha_0) G_m$. Thus $g_2(y, u, t)$ can be chosen as

$$g_2(y, u, t) = \frac{1.5 |e| g_1^3}{e^2 g_1^2 + \delta_1} BND(\dot{e}) + 5 \left| \frac{d g_1}{d t} \right| \quad (41)$$

or, if the simpler expression is desirable

$$g_2(y, u, t) = \frac{1.5}{\delta_1} g_1^2 BND(\dot{e}) + 5 \left| \frac{d g_1}{d t} \right| \quad (42)$$

Note that the choice of bounding function is not unique. The triangle inequality can be used to determine different choices. Usually, the tighter the bounding functions, the better the performance of the robust controller. The parameters chosen in (40) and (42) are experience values. On the basis of simulation results, they can be adopted by the overwhelming majority second

order plants.

Step 4:

If there is enough prior knowledge for plant, we can calculate the desired parameter vector ϑ^* as follows:

$$\vartheta^* = \begin{bmatrix} \vartheta_0^* \\ \vartheta_1^* \\ \vartheta_2^* \end{bmatrix} = \begin{bmatrix} (a_{p1}\alpha_0 + a_{p1}^2 - a_{p1}a_{m1} + a_{p2} - a_{m2} - \alpha_0 a_{m1}) / k_p \\ a_{m1} - a_{p1} \\ (a_{p1}a_{p2} - a_{p2}a_{m2} - a_{p1}\alpha_0^2 - a_{p1}^2\alpha_0 + a_{p1}a_{m1}\alpha_0 + \alpha_0^2 a_{m1}) / k_p \end{bmatrix}$$

It can be used to initiate $\vartheta_i^*(0)$. It is necessary to note that the step 4 is not indispensable for the design of controller. $\vartheta_i^*(0)$ can also be set by the experiment results step by step.

(a) Output response of plant with the P-controller

(b) Outputs of reference model and plant with the MRRC controller

(c) Output track error $e(t)$

(d) Control signal $u(t)$ vs. time t

Fig. 5 The simulation results of the nonlinear plant with the MRRC controller

(a) Comparison between reference model and plant with the proposed controller and the PI-controller

(b) Control signal $u(t)$ vs. time t

Fig. 6 The experiment results of pneumatic servo system with the MRRC controller ($M = 30\text{kg}$)

(a) Comparison between reference model and plant with the proposed controller and the PI-controller

(b) Control signal $u(t)$ vs. time t

Fig. 7 The experiment results of pneumatic servo system with the MRRC controller ($M = 60\text{kg}$)

5. Results of Experiment

5.1 Results of simulation

In order to check the effectiveness of the control scheme presented in Section 4, the simulation was carried out for a second order control plant as follows:

In the experiment, the reference model is defined as following transfer function

(a) Comparison between reference model and plant with the proposed controller and the PI-controller

(b) Control signal $u(t)$ vs. time t

Fig. 8 The experiment results of pneumatic servo system with the MRRC controller ($M = 120\text{kg}$)

$$G_m(s) = 100 / (s + 10)^2$$

and the reference input is $r(t) = \sin(0.5\pi t)$.

The linear part of plant model is selected as the model of pneumatic cylinder with 30kg load mass. It can be modeled by the least square algorithm as

$$G_p(s) = \frac{1359}{s(s + 70)}$$

The lumped disturbance and uncertainty is set as

$$d(y, \dot{y}, t) = \sin(3t) + \frac{\sin(y)}{(1+y^2)}$$

The η of neural network N_{Lc} is set as 0.01 and the control parameters are set as follows:

$$\alpha_0 = 1.0, \vartheta(0) = 0.0, k^*(0) = 15.0, \vartheta_0^*(0) = 12.0, \vartheta_1^*(0) = 5.0,$$

$$\vartheta_2^*(0) = 4.0, \rho(y, t) = 1.0, BND[k_p(0)] = 1500, \delta_1 = \delta_2 = 0.2$$

Simulation results are shown in Fig. 5.

Judged by the results of simulation for a nonlinear plant, we get the satisfied results using the control scheme described in Section 4. It can not only assure the control precise, but also makes the system control continuous uniformly.

5.2 Applying to pneumatic servo system

The simulation results in 5.1 are excellent. In this section, we apply the proposed control scheme to pneumatic servo system described in Section 2. The parameters of controller are set as

$$\alpha_0 = 1.0, \vartheta(0) = 0.0, k^*(0) = 15.0, \vartheta_0^*(0) = 12.0, \vartheta_1^*(0) = 5.0,$$

$$\vartheta_2^*(0) = 4.0, \rho(y, t) = 1.0, BND[k_p(0)] = 1500, \delta_1 = \delta_2 = 0.2$$

where the sampling time is set as $T_s = 2\text{ms}$, the reference input $r(t) = 50\text{ mm}$. Learning rate η of neural network N_{Lc} is set by

0.01. The same reference model is adopted as simulation. The experiment results in varying load mass are shown in Fig. 6, 7 and Fig. 8.

The experiment results in the case of $M = 30\text{kg}$ illustrates that output response of system is excellent. The controller comes over the affection of stick friction and possible nonlinear uncertainties. It must be pointed that the dynamical error always exists because of stick friction. However, in practical application, perhaps, it is more important to ensure the good steady-state tracking precision. In our experiment the steady-state tracking error is always less than $10\mu\text{m}$.

It is well known that the model of plant will be changed along with varying of load mass. In order to get high control precision, generally, we have to tune the control parameters of controller repeatedly. However, we can still obtain satisfied control effects in difference load mass even though using the same control parameters with proposed control scheme.

The experimental results show that the dynamical tracking error becomes great along with increasing of load mass (peak error is less than 2mm in the case of $M=120\text{kg}$ and travel is 50mm), but the steady-state precision is still satisfied (the steady-state tracking error is not greater than $10\mu\text{m}$).

Compared with the results of plant with the PI-controller, we can think that the proposed control scheme is effective for the high precision pneumatic servo system.

6. Conclusions

We have proposed a control scheme for the pneumatic servo system. It can not only guarantee a good control precision but also come over nonlinear uncertainties contained in plant. It can make the pneumatic servo system with satisfied dynamical and steady responses in the case of the load mass varying, even if using the same control parameters. It shows excellent system performance, robustness and good applicability.

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